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Determinants of AI Adoption among Undergraduate Students in Rupandehi District of Nepal

Samjhana Kumari Chaudhary

Abstract
Artificial intelligence (AI) is increasingly used in higher education, but evidence on the factors associated with adoption by undergraduate management students in Nepal remains limited. This study examines associations between awareness of AI tools, digital literacy, internet accessibility, social influence, and self-reported AI adoption among 300 undergraduate management students recruited by convenience sampling in Rupandehi District. Cross-sectional questionnaire data were analyzed using partial least squares structural equation modeling (PLS-SEM), importance-performance map analysis (IPMA), and necessary condition analysis (NCA). In the reported structural model, awareness of AI tools (coefficient = 0.816, $p < 0.001$) and digital literacy (coefficient = 0.109, $p = 0.047$) were positively associated with AI adoption, while internet accessibility (coefficient = -0.098, $p = 0.001$) and social influence (coefficient = -0.102, $p = 0.038$) were negatively associated. The model R-squared was 0.749. Given the cross-sectional convenience sample, these findings are associations and should not be generalized beyond the sample without caution.

Keywords: Artificial intelligence adoption, digital literacy, internet accessibility, awareness of AI tools, social influence.

Samjhana Kumari Chaudhary*
MBA-BF Scholar, Lumbini Banijya Campus, Nepal
**Corresponding author*

1. INTRODUCTION

Artificial Intelligence (AI) has become one of the most influential and promising fields of the recent years. The universities worldwide are capitalizing on AI technology to transform learning and teaching processes and achieve desired learning outcomes. AI-driven technologies have been implemented in higher education and flourishing in tutoring, grading, learning analytics, and generative artificial intelligence to improve learning and teaching processes, as well as provide recommendations and support in learning (Zawacki-Richter et al., 2019; Crompton & Burke, 2023; Ivanova, 2024).

Moreover, AI-powered technologies such as ChatGPT, Google Gemini, Microsoft Copilot, and others have played a significant role in adopting and implementing these technologies in higher education (Dwivedi et al., 2023; Cruz et al., 2024; Li & Wong, 2025). Students are using these AI technologies to write essays, computer codes, conduct research, solve mathematical equations, analyze data sets, and other academic tasks to improve the learning process and achieve positive educational outcomes (Dwivedi et al., 2023; Cruz et al., 2024; Li & Wong, 2025). However, the adoption and implementation of AI technologies in higher education are not at the same level globally. While universities in developed countries are capitalizing on these new technologies, institutions in developing countries are catching up with these developments due to poor digital infrastructure and resources (Kim & Lee, 2022; Erdmann & Toro-Dupouy, 2024). Lack of adequate digital infrastructure and resources has hindered the adoption process among students in developing countries (Ouyang et al., 2022; Mostafavi, 2024). Additionally, the absence of internet

services and sophisticated digital devices has created a digital divide, which has limited most students from using these technologies in their academic pursuits (Ouyang et al., 2022; Mostafavi, 2024). Thus, because of disparities in internet services and digital devices, students in developing countries have been limited from using AI technologies to facilitate their learning processes. Consequently, although these technologies have great potential in higher education, students are still unable to embrace and implement them to improve the learning process, which has prompted many researchers to investigate factors that influence their adoption by students.

Similarly, the situation in Nepal is not an exception to the rule regarding the adoption of these technologies in higher education. Although most students have access to the internet and smartphones, they lack adequate practical knowledge and skills to utilize these technologies to facilitate their studies. Recent surveys report that most Nepalese undergraduate students have very limited knowledge, applicability, and awareness of these technologies (Tripathi, 2024; Poudel & Maharjan, 2025). Additionally, most institutions adopt conventional methods of teaching and learning, whereas the application of AI technologies is in its infancy (Chapagai & Adhikari, 2024). Therefore, the current study aims to reveal influential factors that affect the adoption of these technologies by Bachelor of Management undergraduate students. Previous studies examining factors that influence students' adoption of these technologies have used Technology Acceptance Model (TAM) and Unified Theory of Acceptance and Use of Technology (UTAUT) to provide theoretical background for the study. According to TAM, an individual's behavior to adopt and utilize new technology is determined by its perceived usefulness and ease of use (Davis, 1989). On the other hand, UTAUT model explains users' intention to adopt and utilize an innovation based on performance expectancy, effort expectancy, social influence, and facilitating conditions (Venkatesh et al., 2003). Previous studies on factors affecting students' adoption of these technologies were guided by TAM and UTAUT. This study was inspired by TAM and UTAUT to examine the effect of digital literacy, internet accessibility, AI tools awareness, and social influence on students' adoption of AI technologies. The aforementioned variables were selected based on previous studies conducted on the topic because digital literacy significantly predicted the likelihood of students adopting and utilizing these technologies because learners with adequate practical skills are more likely to adopt these technologies to improve their studies (Adeyinka, 2024; Al-Mughairi & Bhaskar, 2024). Internet accessibility was a critical determinant of the likelihood of students adopting these technologies because most AI-powered technologies require internet services and appropriate digital infrastructure to function properly (Mostafavi, 2024). Additionally, poor awareness of these technologies' applicability reduced the likelihood of students adopting and utilizing the tools to enhance their studies (Bouebdallah, 2025; Alshammari, 2025). Finally, social influence significantly predicted positive attitudes among students towards adopting these technologies (Ngo et al., 2025; Ivanov, 2024). Thus, previous studies conducted to reveal factors influencing students' adoption of AI technologies have been conducted in developed countries. There is a need to reveal the effect of these variables on students' adoption of these technologies in developing countries.

Although there is a need to examine factors that influence students' adoption of these technologies, there is limited information on the issue, specifically in developing countries. Therefore, this study aimed to contribute to the body of knowledge by investigating the effect of digital literacy, internet accessibility, awareness of AI tools, and social influence on students' adoption of AI technologies. In addition, although previous studies have revealed factors influencing university students' adoption of AI technologies, several research gaps remain. Firstly, most previous studies

examining influences of these technologies on students were conducted in developed countries, and there is limited information on the issue in developing countries such as Nepal (Ouyang et al., 2022; Crompton & Burke, 2023; Tripathi, 2024). Therefore, there is a need for more studies to reveal factors influencing students' adoption of these technologies in developing countries. Specifically, there is limited information about the extent to which digital literacy, internet accessibility, awareness of AI tools, and social influence predicted the likelihood of adopting these technologies by by Bachelor of Management undergraduate students in Nepal (Tripathi, 2024; Poudel & Maharjan, 2025).

Secondly, most previous studies examining factors influencing students' adoption of AI technologies mainly focused on establishing the existence of a direct relationship between the independent and dependent variables by applying traditional statistical techniques in data analysis (Adeyinka, 2024; Al-Mughairi & Bhaskar, 2024; Ngo et al., 2025). Therefore, there is a need to conduct more studies to examine the relative importance of each of the predictors of students' adoption of these technologies. In addition, most researchers have failed to explore the conditions that must be met for the adoption of these technologies to take place (Ringle & Sarstedt, 2016; Dul, 2016). This study aimed to fill this research gap by integrating Importance-Performance Map Analysis (IPMA) and Necessary Condition Analysis (NCA) with Partial Least Squares Structural Equation Modeling (PLS-SEM) to provide managerial and policy implications for promoting students' adoption of AI technologies.

This study examines associations between digital literacy, internet accessibility, awareness of AI tools, social influence, and self-reported AI adoption among Bachelor of Management undergraduate students in Rupandehi District, Nepal. The study uses partial least squares structural equation modeling (PLS-SEM) to estimate the relationships among the study variables (Hair et al., 2022), importance-performance map analysis (IPMA) to assess predictor importance and performance (Ringle & Sarstedt, 2016), and necessary condition analysis (NCA) to examine conditions associated with higher adoption (Dul, 2016).

1.1 Research Questions

RQ1: *How are digital literacy, internet accessibility, awareness of AI tools, and social influence associated with AI adoption among Bachelor of Management undergraduate students in Rupandehi District, Nepal?*

RQ2: *Which factors, if any, are necessary for achieving higher levels of AI adoption among Bachelor of Management undergraduate students?*

1.2 Research Objectives

RO.1 *To examine the associations between digital literacy, internet accessibility, awareness of AI tools, social influence, and AI adoption among Bachelor of Management undergraduate students.*

RO.2 *To assess the relative importance and performance of the predictors of AI adoption using IPMA and examine whether any predictors constitute necessary conditions using NCA.*

2. LITERATURE REVIEW

2.1 Theoretical Review

The acceptance of new technology innovations in higher education has been examined extensively using technology acceptance models. Technology Acceptance Model (TAM) and Unified Theory

of Acceptance and Use of Technology (UTAUT) are the predominant models that have been used to understand and predict individual acceptance and use of novel technology innovations (Davis, 1989; Venkatesh et al., 2003). This paper will discuss TAM and UTAUT's role in deciphering the determining factors of student acceptance of artificial intelligence technologies.

Technology Acceptance Model (TAM) was proposed by Davis (1989). TAM theorized that perceived usefulness and perceived ease of use of technology predicted the acceptance of technology innovation by an individual (Davis, 1989). Perceived usefulness consisted of individuals' beliefs that adopting new technology would improve their performance, while perceived ease of use comprised of the beliefs about the ease of using the technology. With regard to higher education, students will adopt artificial intelligence technologies if they perceive that these innovations will improve their learning processes, grades, or help them achieve their academic goals (Kim & Lee, 2022; Li &Wong, 2025).

Unified Theory of Acceptance and Use of Technology (UTAUT) was developed by Venkatesh et al. (2003). UTAUT provided a consolidated framework that explained the various technology acceptance models that had been used to predict and explain individuals' acceptance and use of technology innovations (Venkatesh et al., 2003). It was theorized that performance expectancy, effort expectancy, social influence, and facilitating conditions were the four constructs that predicted technology adoption by individuals (Venkatesh et al., 2003). Performance expectancy was described as the individual's belief that adopting the technology will improve their performance levels using the innovation. Effort expectancy consisted of the individual's expectations that the new technology will be easy to use; facilitating conditions referred to students' perceptions that adopting the technology would require the individual to invest time and effort. In addition, social influence comprised of the extent to which students were persuaded to adopt the technology innovations based on their friends', parents', or colleagues' persuasion (Venkatesh et al., 2003).

Technology Acceptance Model (TAM) and Unified Theory of Acceptance and Use of Technology (UTAUT) were proposed as theoretical models that predicted students' technology adoption. With reference to the theories and the above discussion, it was hypothesized that digital literacy, internet accessibility, awareness of AI tools, and social influence were the determining factors of students' AI adoption. Digital literacy was the students' cognitive abilities, confidence, and competence in using the digital technologies (Adeyinka, 2024; Al-Mughairi & Bhaskar, 2024). Students with high levels of digital literacy adopted AI technologies faster than their less literate counterparts. This is because students who were digitally literate accessed technology confidently and used it to achieve their goals instead of those with lesser digital literacy knowledge (Adeyinka, 2024; Al-Mughairi & Bhaskar, 2024). Past studies have shown the role of digital literacy in students' AI adoption (Adeyinka, 2024; Al-Mughairi & Bhaskar, 2024). In TAM, digital literacy predicted students' ease of use of artificial intelligence technologies. According to UTAUT, digital literacy was positively related to students' effort expectancy when using AI technologies.

Internet accessibility was students' availability to the internet and other digital resources. Some AI applications are only accessible by stable internet connection (Mostafavi, 2024; Erdmann & Toro-Dupouy, 2024). Students who had greater access to the digital resources and the internet compared to their counterparts used AI technologies to gain knowledge and excel academically since they could easily access the online tools. According to past research, internet accessibility influenced the facilitating conditions of students' adoption of artificial intelligence technologies

(Venkatesh et al., 2003). Awareness of AI tools consisted of students' awareness of the artificial intelligence applications and their academic usefulness. Students who were highly aware of the benefits of adopting AI influenced their less aware counterparts to embrace the technologies (Alshammari, 2025; Bouebdallah, 2025). The awareness of students of the AI tools predicted their perception of the usefulness of the tools, which consequently predicted their adoption of the technologies. This is because students' awareness level of AI tools influenced their beliefs regarding the technologies' potential to improve their performance as discussed in TAM.

Social influence was the impact of the social and academic environment on students, for example, their adoption of AI technologies. Students were influenced to adopt AI technologies when their social network encouraged them to use the innovations (Ngo et al., 2025; Ivanov, 2024). For instance, Ngo et al. (2025) and Ivanov (2024) showed that students who were motivated by their friends and teachers to embrace new technologies were more likely to adopt the technologies than those who lacked such encouragement. The concept of social influence had been identified as a critical predictor of students' technology adoption (Ngo et al., 2025; Ivanov, 2024). Social influence directly predicted the intention of students to adopt artificial intelligence technologies. It was considered as one of the key constructs that predicted individuals' adoption of technology innovations according to the UTAUT framework (Venkatesh et al., 2003). Socio-economic conditions influenced students' extent of technology adoption and use (Ouyang et al., 2022; Crompton & Burke, 2023).

To conclude, TAM and UTAUT had been used as theoretical models to predict students' AI technology adoption. As discussed in the above paragraphs, the study used the theories to hypothesize the determining factors of AI technologies among the students of the Rupandehi District, Nepal.

2.2 Empirical Review

The factors influencing students' consideration of adopting artificial intelligence (AI) were highlighted in the current study. First of all, the study identified that digital literacy was one of the critical individual factors that influenced students' intention to use artificial intelligence. The justification is that with high levels of digital competence, students gain confidence in using artificial intelligence for research, study, and learning. In addition, students with high levels of digital literacy are more likely to perceive artificial intelligence as convenient and valuable technologies that serve their interests more than those with average and low levels of digital competence (Adeyinka, 2024; Al-Mughairi and Bhaskar, 2024). Therefore, it is concluded that individual factors affecting students' consideration of adopting artificial intelligence for higher education purposes outweigh other factors, thereby predicting students' intention to adopt the technologies at the highest level.

2.2.1 Awareness of AI tools and AI adoption

One of the factors hypothesized to predict students' intention to adopt AI is their awareness of artificial intelligence tools. The rationale behind this is that students' awareness of the tools that can be used to perform specific tasks, such as writing essays, calculations, and other academic activities enhances the likelihood of adopting the technology to achieve the intended purposes. Indeed, selected previous research has demonstrated that students' awareness of the potential of artificial intelligence positively predicts their attitude toward adopting the technology and its utilization to perform specific tasks (Alshammari, 2025; Bouebdallah, 2025).

H1: Awareness of AI tools positively influences AI adoption by Bachelor of Management undergraduates.

2.2.2 Digital literacy and AI adoption

Another factor hypothesized to predict students' intention to adopt AI is their digital literacy. For the current study, digital literacy was envisioned as the students' proficiency in utilizing the tools to achieve the intended objectives. Therefore, digitally literate students are individuals with the required knowledge and skills to use existing technologies, including artificial intelligence to perform specific tasks, such as research, essay writing, and calculations among other academic activities. Indeed, previous studies have shown that students' digital literacy skills positively predict their willingness to adopt artificial intelligence (Adeyinka, 2024; Al-Mughairi and Bhaskar, 2024).

H2: Digital literacy positively influences AI adoption by undergraduates.

2.2.3 Internet accessibility and AI adoption

The third factor hypothesized to predict students' intention to adopt AI is internet accessibility. Internet accessibility was expected to predict students' willingness to adopt artificial intelligence because it would empower them to use online softwares and applications to improve their academic performance. In fact, most previous studies have shown that internet accessibility significantly and positively predicts students' willingness to adopt artificial intelligence (Mostafavi, 2024; Erdmann & Toro-Dupouy, 2024).

H3: Internet accessibility significantly and positively predicts AI adoption by Bachelor of Management undergraduates.

2.2.4 Social influence and AI adoption

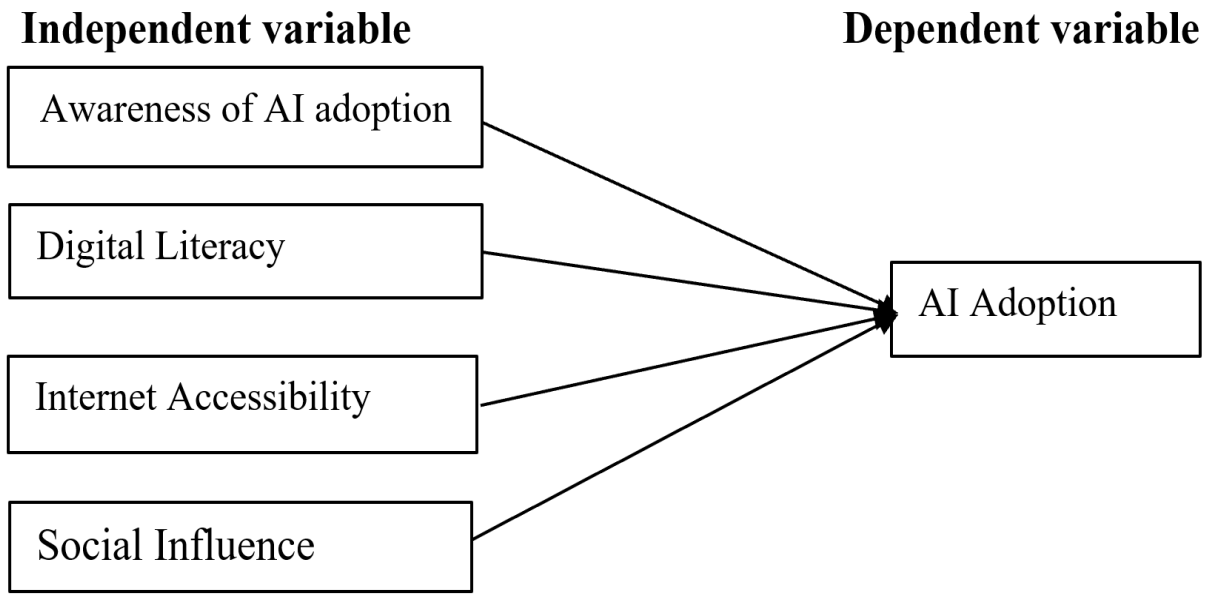
The final factor hypothesized to predict students' intention to adopt AI is social influence. For the current study, social influence was envisioned as the extent to which a student can be persuaded, encouraged, or motivated by teachers, peers, or the environment to perform a certain behavior, such as adopting artificial intelligence to improve their academic performance. For example, encouragement and persuasion from peers and teachers regarding the benefits of adopting artificial intelligence can improve the students' awareness of the benefits of the technology and change their perception of how easy or difficult it is to adopt the innovation, thereby influencing their intention to use the technology to enhance their academic performance. Indeed, recent studies have shown that social influence significantly and positively predicts students' willingness to adopt artificial intelligence (Ngo et al., 2025; Ivanov, 2024).

H4: Social influence significantly and positively predicts AI adoption by Bachelor of Management undergraduates.

2.3 Conceptual framework

The conceptual framework is provided below. From the diagram, it is evident that some of the proposed relationships can partly explain how the predictor variables influence the students' perception and attitude towards adopting AI and their intentions to use the technology. In other words, the conceptual framework below illustrates how social influence, digital literacy, and internet accessibility can influence Bachelor of Management undergraduate students' adoption of artificial intelligence.

Figure 1 - *Conceptual framework*



Source: Adeyinka, 2024; Alshammari, 2025; Al-Mughairi & Bhaskar, 2024; Bouebdallah, 2025; Davis, 1989; Ivanov, 2024; Mostafavi, 2024; Ngo et al., 2025; Ouyang et al., 2022; Venkatesh et al., 2003;

3. RESEARCH METHODOLOGY

3.1 Research Designs

This study used a quantitative, descriptive, cross-sectional design. Given the observational data, the analyses estimate associations and do not establish causal effects.

The data were collected at a single point in time. This cross-sectional design describes respondents and estimates associations among the study constructs; it cannot establish temporal order or causal effects.

3.2 Population and Sample

The target population for this study comprised undergraduate management students studying in colleges and universities in Rupandehi District, Nepal. These students were considered because they engaged with online technology, software, and AI-enabled devices in their academic programs. This rationale explains why this particular group of students was selected because they interacted with AI frequently compared to other demography.

The study included 300 respondents. Because participants were recruited using convenience sampling, the sample size alone does not establish representativeness or support generalization to the full target population. The sample-size rationale should be supported by an analysis appropriate to the PLS-SEM model rather than by a respondent-to-item rule alone.

Participants were recruited using non-probability convenience sampling. This approach is efficient but may introduce selection bias and does not support statistical generalization to the target population. Findings should therefore be interpreted as applying to the respondents in this sample, subject to the study limitations.

3.3 Nature and Sources of Data

Primary data were collected from undergraduate management students in Rupandehi District using a structured questionnaire. Further details on recruitment and data collection should be provided so that the sampling and response process can be evaluated.

The sample-size rationale and participant characteristics are described in Section 3.2.
The recruitment approach and its limitations are described in Section 3.2.

3.4 Data Collection Instrument

This study used a questionnaire as a data collection tool because it could generate reliable and valid data for a quantitative study. The questionnaire comprised close-ended questions to measure the key constructs identified and stated in the research model.

The level of agreement and disagreement of the respondents with the items in the questionnaire was measured using a Likert scale. Each item used a seven-points Likert scale ranging from 1 to 7 with 1 indicating strongly disagree and seven meaning strongly agree. This seven-point Likert scale was ideal for this study because it allowed the respondents to provide their view and opinion on the items included in the questionnaire clearly and specifically. Besides, this Likert scale was better compared to the five-point, nine-point, and eleven-point because it had a higher degree of variability to capture the view of the respondents (Hair et al., 2021).

The questionnaire used in this study was constructed by reviewing and modifying existing items used in previous studies related to this research. A pilot study was conducted to examine the relevance, validity, and overall effectiveness of the questionnaire. The pilot study allowed the researcher to revise and restructure the questionnaire according to the needs of the actual study. This data collection tool had several strengths, including being able to collect data from 300 respondents within a short time. This consideration made it adequate and appropriate to use the questionnaire to gather information from the large target population (Hair et al., 2021).

4. RESULT AND ANALYSIS

4.1 Respondents Profile

Table 1 - *Respondents' profile/Descriptive statistics of participants*

Demographics	**Data Presentation**	
Gender	**Frequency**	**Percent**
Female	227	75.67
Male	73	24.33
Experience	**Frequency**	**Percent**
Yes	296	98.7
No	4	1.3
Age	**Frequency**	**Percent**
Below 20	192	64
20-22	42	14
23-25	52	17.3
Above 25	14	4.7
Education	**Frequency**	**Percent**
BBA	38	12.7
BBM	24	8.0
BBS	221	73.7
BIM	10	3.3
BHM	7	2.3

Table 1 below presents the summary statistics of the respondents who participated in the study. It can be noted that out of the 300 respondents 227 (75.7%) were female while 73 (24.3%) were male. In terms of their age distribution, 64% of the respondents were below 20 years followed by those aged 23-25 years with 17.3% and those aged 20-22 years with 14%. Finally, 4.7% of the respondents were aged above 25 years.

Similarly, in terms of the respondent's program, it was found that majority of the respondents (73.7%) were pursuing Bachelor of Business Studies. On the other hand, 12.7%, 8%, 3.3%, and 2.3% of the respondents were studying Bachelor of Business Administration, Bachelor of Business Management, Bachelor of Information Management, and Bachelor of Hotel Management respectively.

Finally, in terms of their experience with Artificial Intelligence (AI), 296 respondents (98.7%) responded that they had previous experience working with AI while 4 respondents (1.3%) had no previous experience. From the description of the sample above, it suffices to say that the sample is suitable for the purpose of this study. This is because the respondents are more experienced with AI technologies and therefore their responses are more informative in identifying factors which influence their adoption of AI by the respondents who are studying management programs in Rupandehi District, Nepal.

4.2 Common Method Bias (CMB)

Table 2 - *Variance Explained*

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	12.279	49.115	49.115	12.279	49.115	49.115
2	3.006	12.025	61.14			
3	1.612	6.448	67.588			
4	1.117	4.468	72.055			
5	0.907	3.629	75.684			
6	0.699	2.796	78.48			
7	0.67	2.681	81.161			
8	0.499	1.995	83.156			
9	0.465	1.858	85.014			
10	0.423	1.692	86.706			
11	0.383	1.532	88.239			
12	0.338	1.352	89.59			
13	0.314	1.257	90.848			
14	0.293	1.171	92.019			
15	0.27	1.081	93.1			
16	0.255	1.022	94.122			
17	0.231	0.924	95.046			
18	0.205	0.819	95.866			
19	0.195	0.779	96.645			
20	0.186	0.742	97.387			
21	0.165	0.659	98.047			
22	0.149	0.594	98.641			
23	0.125	0.501	99.142			

24	0.12	0.481	99.623			
25	0.094	0.377	100			

Extraction Method: Principal Component Analysis.

In order to assess whether common method bias (CMB) might have distorted the results of the study, the Harman's single factor test was conducted using the Principal Component Analysis (PCA). The results of the test are presented in Table 2 below, where the numbers represent the percentage of variance explained by each factor.

The first unrotated factor accounts for 49.115% of the variance reported in Table 2, below the 50% screening threshold cited by Podsakoff and Organ (1986). This result does not, by itself, rule out common method bias or confirm the validity of the measures. It should be treated as a limited diagnostic and interpreted alongside the study design and other procedural or statistical checks.

4.3 Measurement Item Assessments

The measurement items used to assess the constructs related to AI adoption among undergraduate students were evaluated by examining their indicator reliability. Indicator reliability was assessed using outer loadings, with values exceeding the recommended threshold of 0.70 indicating that each measurement item adequately represented its corresponding construct (Sarstedt et al., 2017).

As presented in Table 3, all measurement items achieved outer loading values greater than 0.70, demonstrating satisfactory indicator reliability. These results indicate that each indicator made a meaningful contribution to its respective construct. Consequently, all measurement items met the recommended criterion and were retained for subsequent analyses.

Table 3 - *Assessment of scale items or measurement model assessment*

	Outer loadings	**VIF**	**Mean**	**Standard deviation**
AAD1	0.898	3.265	5.607	1.451
AAD2	0.896	3.406	5.063	1.762
AAD3	0.792	2.441	4.983	1.806
AAD4	0.856	2.63	5.107	1.857
AAD5	0.827	2.305	5.547	1.47
AIT1	0.82	1.88	5.52	1.552
AIT2	0.801	2.394	5.693	1.51
AIT3	0.869	3.025	5.55	1.549
AIT4	0.862	3.546	4.92	1.753
AIT5	0.773	2.634	4.567	1.724
DL1	0.871	2.938	5.94	1.399
DL2	0.913	4.092	5.803	1.5
DL3	0.916	4.333	5.697	1.655
DL4	0.742	1.879	5.01	1.786
DL5	0.776	1.736	5.493	1.714
IA1	0.895	3.015	3.313	1.857
IA2	0.876	2.905	3.68	1.93
IA3	0.837	2.325	3.643	2.037
IA4	0.802	2.253	4.123	1.941
IA5	0.913	3.905	3.797	1.952
SI1	0.84	2.243	5.12	1.697

SI2	0.797	2.137	5.193	1.797
SI3	0.847	2.297	5.467	1.508
SI4	0.782	1.86	5.767	1.56
SI5	0.799	1.772	5.163	1.591

Table 3 reports outer loadings ranging from 0.742 to 0.916. On the values shown in the table, all listed indicators exceed 0.70. This range conflicts with the previously reported range of 0.699 to 0.933 and the statement that DL5 loaded at 0.699; these figures must be reconciled with the original measurement-model output before publication.

Table 3 reports item means and standard deviations separately from outer loadings; these descriptive statistics do not establish the stability of the bootstrapping procedure. The item-level VIF values shown in the table range from 1.736 to 4.333. Please clarify how these indicator VIFs were calculated and distinguish them from collinearity diagnostics for the structural predictors.

Consequently, most of the items met the criteria of indicator reliability, and all items were suitable for further assessment of the measurement model, including reliability, validity, and structural model.

4.4 Quality Criteria Assessment

Cronbach alpha values in Table 4 range from 0.873 to 0.916, exceeding the commonly used 0.70 guideline for internal consistency. Please cite an appropriate methodological source for this threshold.

Convergent validity was evaluated using composite reliability (CR) scores, which were denoted by rho_A and rho_C, and average variance extracted (AVE). According to the recommendations of researchers, Saari et al. (2021) and Hair and Alamer (2022), all rho_A and rho_C scores were within the acceptable range of 0.70 to 0.95, signifying that the constructs possessed adequate reliability. Concurrently, the AVE scores of all constructs were above the threshold value of 0.5, suggesting that more than half of the variance was captured by each indicator. Thus, it can be concluded that all constructs displayed satisfactory convergent validity and were fit for further analysis in the structural model.

Table 4 - *Construct Reliability and Validity/Inner Model Assessment /Convergent Validity*

	Cronbach 's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
AAD	0.908	0.916	0.931	0.73
AIT	0.883	0.893	0.914	0.682
DL	0.899	0.907	0.926	0.717
IA	0.916	0.929	0.937	0.749
SI	0.873	0.882	0.907	0.662

Table 4 below contains information on construct reliability and convergent validity of all constructs used in the study. First of all, Cronbach’s alpha value for all constructs varied from 0,873 to 0,916, which is significantly higher than the acceptable minimum level of 0,7. This suggests that there is a satisfactory level of consistency across items within each of the constructs.

Composite reliability was also satisfactory, as demonstrated by the composite reliability values, rho_A, varying from 0,882 to 0,929, while rho_C ranged from 0,907 to 0,937. For all constructs,

composite reliability exceeded the minimum level of 0,7. Finally, the AVE values ranged from 0,662 to 0,749, which is considerably higher than the required level of 0,5. This suggests that each item explains more than half of the variance. Thus, all constructs met the requirements for convergent validity.

Based on the analysis, a conclusion can be drawn that the model demonstrated an acceptable level of construct reliability and was therefore fit for the next stage of analysis, namely structural model testing and estimation.

Table 5 - *Heterotrait-monotrait ratio (HTMT) of correlations*

	AAD	AIT	DL	IA	SI
AAD					
AIT	0.83				
DL	0.788	0.888			
IA	0.395	0.37	0.451		
SI	0.702	0.868	0.808	0.516	

Table 5 below provides the Heterotrait–Monotrait (HTMT) ratio of correlations employed to assess the discriminant validity of the measurement model. According to Henseler et al. (2015), HTMT ratios should ideally be less than 0.85. Values below 0.9 also suggest successful discriminant validity (Henseler et al., 2015).

The HTMT values reported in Table 5 range from 0.370 to 0.888. Although all are below 0.90, the AIT-DL value of 0.888 exceeds the stricter 0.85 guideline cited above and is close to 0.90. Discriminant validity should therefore be interpreted cautiously, and the authors should report the criterion applied and any relevant inferential assessment.

Table 6 - *Fornell- Larcker Criterion*

	AAD	AIT	DL	IA	SI
AAD	0.855				
AIT	0.858	0.826			
DL	0.728	0.799	0.847		
IA	-0.377	-0.345	-0.42	0.866	
SI	0.653	0.772	0.727	-0.47	0.813

Table 6 presents the Fornell-Larcker criterion for discriminant validity. The diagonal entries are the square roots of the AVE values, and the off-diagonal entries are construct correlations.

The values in Table 6 do not satisfy the Fornell-Larcker criterion for every construct pair: the AAD-AIT correlation (0.858) slightly exceeds the square root of AVE for AAD (0.855). This pair should be investigated and the discriminant-validity conclusion revised as appropriate before structural results are interpreted.

4.5 Structural Model Assessment

Table 7 - *Model Fit*

	Saturated model	**Estimated model**
SRMR	0.083	0.083
d_ULS	2.258	2.258
d_G	0.97	0.97

Chi-square	1548.12	1548.12
NFI	0.772	0.772

Table 7 reports the model-fit statistics for the saturated and estimated models: SRMR = 0.083, d_ULS = 2.258, d_G = 0.970, chi-square = 1548.12, and NFI = 0.772. The table does not report f-squared effect sizes; those are presented in Table 8.

The manuscript should state and justify the evaluation criteria for these fit indices. In particular, NFI is reported as 0.772; its adequacy should not be asserted without a stated benchmark and rationale. Please also explain how the d_ULS and d_G values were evaluated.

The predictor-specific effect sizes are reported separately in Table 8 and should be distinguished from the structural path coefficients and their statistical significance in Table 10.

Table 8 - *F-square (Effect Size)*

	f-square	Effects
AIT -> AAD	0.741	Large
DL -> AAD	0.015	No effect
IA -> AAD	0.029	Small
SI -> AAD	0.014	No effect

Table 8 presents the effect sizes (f-squared) of the exogenous constructs on AI adoption.

Digital literacy (f-squared = 0.015) and social influence (f-squared = 0.014) have small effect sizes under the stated criteria. Effect size is distinct from statistical significance: both paths are reported as statistically significant in Table 10, and their direction and uncertainty should be interpreted from those estimates.

In summary, awareness of AI tools has the largest reported f-squared value (0.741). Internet accessibility has a small f-squared value (0.029), while digital literacy and social influence have values below 0.02. These effect-size results should not be conflated with the statistical significance of the paths reported in Table 10.

Table 9 - *R-square*

	R-square	R-square adjusted	Predictive Power
AAD	0.749	0.746	Strong

The R-squared value of 0.749 indicates that the four predictors account for 74.9% of the in-sample variance in the AI adoption construct. The remaining variance is not explained by this model; it should not be attributed solely to omitted independent variables.

The adjusted R-squared (0.746) is close to R-squared (0.749). This small difference indicates little change after adjustment for the number of predictors, but does not by itself establish model quality or out-of-sample predictive performance.

4.7 Structural Equation Model

Figure 2 - *Structure Model*

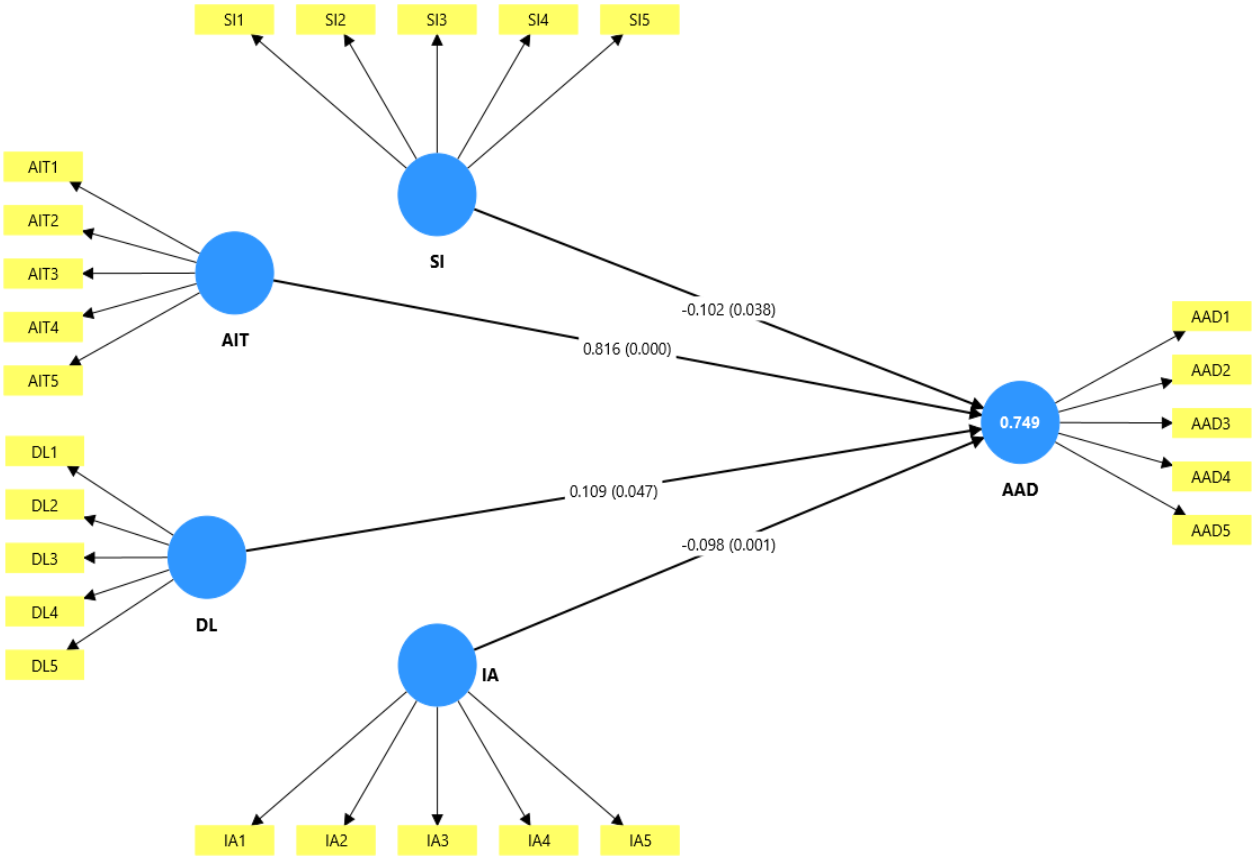


Table 10 - *Hypothesis Testing using Bootstrapping*

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	Decision
H1: AIT -> AAD	0.816	0.811	0.063	12.908	<0.001	Supported
H2: DL -> AAD	0.109	0.113	0.055	1.988	0.047	Supported
H3: IA -> AAD	-0.098	-0.098	0.03	3.233	0.001	Not Supported
H4: SI -> AAD	-0.102	-0.1	0.049	2.074	0.038	Not Supported

The negative path coefficients for Internet Accessibility (β=−0,098, p=0,001) and Social Influence (β=−0,102, p=0,038) indicate that, while controlling the effect of Awareness of AI Tools and Digital Literacy, Internet Accessibility and Social Influence negatively predicted AI Adoption by undergraduate students. Both variables significantly contributed to the prediction of the dependent variable at the p<0,05 level, which means that the influence of these predictors on the outcome variable in the proposed structural model was negative. Although the initial expectation was to observe positive relationships between these variables and AI Adoption, the results were the opposite.

4.8 Importance-Performance Map Analysis (IPMA)

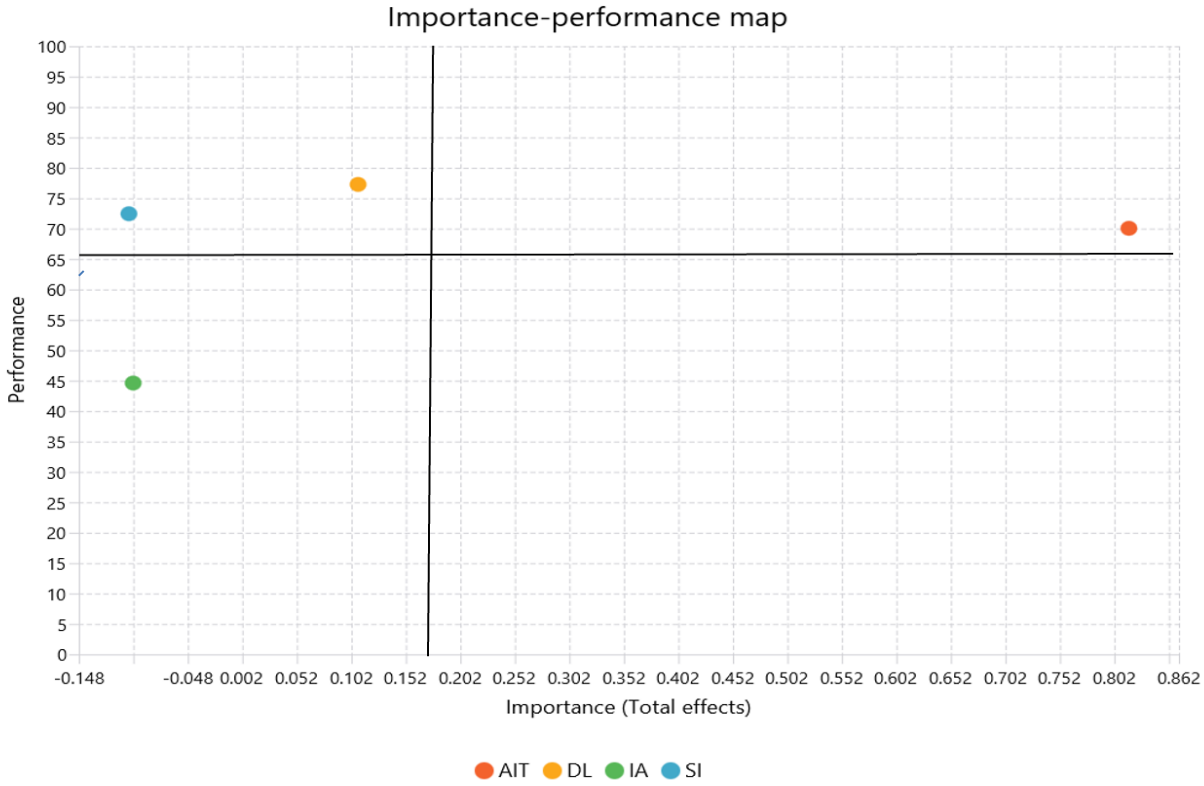
Table 11 - *Importance Performance Map Analysis (IPMA)*

	Importance	Performance
AIT	0.816	70.06
DL	0.109	77.28
IA	-0.098	44.61
SI	-0.102	72.45

Table 11 above reports the results of the Importance Performance Map Analysis of the predictors of AI Adoption. The results indicate that out of all the predictors of AI Adoption, Awareness of AI Tools had the highest importance (0.816) and a high performance (70.06). This suggests that Awareness of AI Tools has the greatest potential to improve AI Adoption among the students.

Digital Literacy had the lowest importance (0.109) but the highest performance (77.28). This implies that respondents reported a high level of digital literacy levels among the undergraduate students. However, the construct had a minimal influence on the rate of AI Adoption. On the other hand, Social Influence and Internet Accessibility had negative importance of −0.102 and −0.098, respectively. In addition, the performance of Internet Accessibility was the lowest (44.61) compared to the other predictors. Overall, the results of the IPMA analysis reveal that Awareness of AI Tools is the most important driver of AI Adoption among undergraduate students. However, the results also indicate that Digital Literacy had the highest performance, although it had the lowest importance level among the predictors of AI Adoption. Consequently, increasing the performance of Digital Literacy beyond its current levels will have a minimal effect on improving AI Adoption compared to Awareness of AI Tools.

Figure 3 - *Importance-Performance Map*



4.9 Necessary Condition Analysis (NCA)

Table 12 - *Bottleneck percentile*

	LV scores - AIT	LV scores - DL	LV scores - IA	LV scores - SI
0.00%	NN	NN	NN	NN
10.00%	2	NN	NN	0.6
20.00%	2	NN	NN	3.3
30.00%	7.6	NN	NN	5
40.00%	9.3	5.6	NN	6.3

50.00%	10	5.6	NN	6.3
60.00%	10	5.6	NN	7.3
70.00%	10	5.6	NN	7.3
80.00%	10	5.6	NN	7.3
90.00%	16	5.6	NN	13
100.00%	16	5.6	NN	13

Table 12 presents the findings of the NCA analysis (bottleneck analysis). As can be seen from the table, none of the predictors were necessary for achieving a 0% level of AI Adoption, as all the constructs were classified as Not Necessary (NN).

According to Table 12, social influence has a reported bottleneck value beginning at the 10% target level, whereas awareness of AI tools is marked NN at 10% and 20% and has a reported value from 30% onward. Digital literacy is marked NN through 30% and has a reported value from 40% onward; internet accessibility is marked NN at every target level.

The bottleneck values for awareness of AI tools and social influence rise at higher target levels, while the reported digital-literacy value remains 5.6 from 40% onward. The values in Table 12 are presented as latent-variable scores; avoid appending percent signs unless the authors verify that this is the correct scale.

In summary, the reported NCA results identify social influence as a bottleneck from the 10% target level, awareness of AI tools from 30%, and digital literacy from 40%; internet accessibility is marked NN throughout. These are sample-specific bottleneck results, and their substantive interpretation depends on the NCA scoring, ceiling-line procedure, and units, which should be reported.

5. DISCUSSION AND CONCLUSION

5.1 Discussion

This study examined associations between four predictors and self-reported AI adoption among undergraduate management students. In the combined structural model, awareness of AI tools (coefficient = 0.816, $p < 0.001$) and digital literacy (coefficient = 0.109, $p = 0.047$) were positively associated with adoption, while internet accessibility (coefficient = -0.098, $p = 0.001$) and social influence (coefficient = -0.102, $p = 0.038$) were negatively associated. These results are cross-sectional associations, not causal effects.

The current study found a positive relationship between AIT and the intention to adopt AI, which corroborated the results of previous studies (Alshammari, 2025; Bouebdallah, 2025). Indeed, in previous studies AIT was a significant and positive predictor of intention to use AI for the purpose of education (Alshammari, 2025; Bouebdallah, 2025). The positive relationship between DL and intention to adopt AI was also consistent with the results of Adeyinka (2024) and Al-Mughairi & Bhaskar, (2024), as in the present study. Specifically, prior research found that DL positively and significantly predicted the ability of students to discover, explore and exploit artificial intelligence for academic purposes (Adeyinka, 2024; Al-Mughairi & Bhaskar, 2024). Therefore, the findings of the current study on the relationships between AIT and the intention to adopt AI and between DL and the intention to adopt AI added to the body of knowledge by providing empirical evidence.

However, the current study found that IA and SI negatively and significantly predicted the intention of undergraduates to adopt AI, which ran counter to the results of previous studies (Alshammari, 2025; Adeyinka, 2024; Al-Mughairi & Bhaskar, 2024; Bouebdallah, 2025). Indeed, prior research found that IA positively and significantly predicted students' intention to adopt AI for educational purposes (Alshammari, 2025; Adeyinka, 2024). Likewise, previous studies found that SI positively and significantly influenced students' intention to adopt AI for educational purposes (Al-Mughairi & Bhaskar, 2024; Bouebdallah, 2025). Thus, the current findings on the relationships between IA and the adoption of AI and between SI and the adoption of AI contradicted the results of previous studies, which could be considered a limitation of the current study. Nonetheless, the current study provided an explanation for this contradiction. Specifically, IA may not contribute to the adoption of AI if students use the online resources for entertainment purposes rather than for academic purposes. In other words, students' Internet accessibility may facilitate recreational activities instead of enhancing their capacity to use artificial intelligence for learning, research, and problem-solving. Likewise, SI may not lead to higher levels of AI adoption if the recommendations are not oriented towards academic purposes, such as avoiding plagiarism among students.

The IPMA results in Table 11 report importance values of 0.816 for AIT, 0.109 for DL, -0.098 for IA, and -0.102 for SI; the negative values should be interpreted as negative associations, not positive priorities. Table 12 reports the NCA bottleneck pattern separately. These analyses do not establish that increasing any predictor will cause adoption to rise. Recommendations should reflect the observed directions and the limitations of the cross-sectional convenience sample.

5.2 Conclusion

This study examined factors associated with self-reported AI adoption among 300 undergraduate management students recruited by convenience sampling in Rupandehi District, Nepal. In the reported model, awareness of AI tools and digital literacy were positively associated with adoption, while internet accessibility and social influence were negatively associated. Awareness of AI tools had the largest reported path coefficient, and the model R-squared was 0.749. Because the study is cross-sectional and uses a non-probability sample, the findings should not be interpreted causally or generalized to all students or universities in Nepal. Further research using broader sampling frames and longitudinal or comparative designs is warranted.

5.3 Implications

5.3.1 Theoretical Implications

The paper extended TAM and UTAUT applications to the AI adoption case among university students in Nepal and contributed to theories by empirically determining the linkages among determinants and adoption behaviours. Specifically, besides confirming several positive and negative relationships between constructs and intention to adopt AI, the paper revealed discrepancies in influence patterns, thus contributing to TAM and UTAUT's development. In addition, the findings highlight the importance of investigating cultural influences on determinants when determining the intention to adopt AI among students in Nepal. Lastly, the research provided insights into the factors affecting Nepalese undergraduates' AI adoption behaviours, thus demonstrating how theories can effectively predict these behaviours while considering cultural influences.

5.3.2 Practical Implications

The results of the paper can be applied by different stakeholders in the field of higher education. First of all, universities should conduct awareness campaigns, organize workshops and training sessions to improve students' knowledge of artificial intelligence and its application in academic settings. Second, students need to be educated about digital literacy and empowered to operate using digital technology. Instructors should also remind students of the ethical use of AI-driven technologies and advise them on how to avoid academic misconduct when applying such technologies in their assignments. Besides, due to the study's unexpected results concerning Internet Accessibility and Social Influence, it is relevant for universities to reconsider how students interact with the online environment and how their behavior is affected by their social groups. By implementing these solutions, academic institutions can play a leading role in ensuring that their students adopt artificial intelligence responsibly and sustainably, which would contribute to the quality of their technology-enabled education.

5.4 Limitations and Future Research

This study has several limitations that should be noted while considering the results of the research. First, the study was conducted among the undergraduate students of Rupandehi District, Nepal, so the findings cannot be generalized to other places, universities and levels of education. Secondly, the study used a cross-sectional design, meaning that the information gathered reflected students' views at one moment. As such, it was not possible to establish how students' perspectives evolved throughout time or whether any shifts in AI adoption attitudes occurred. Thirdly, the paper explored only four out of many possible determinants of AI adoption, including Awareness of AI Tools, Digital Literacy, Internet Accessibility, and Social Influence. Despite the fact that the research identified several significant predictors of AI adoption, there are likely other variables that influence students' adoption behavior's in higher education as well.

5.5 Future Research

These limitations motivate further research. Future studies could examine additional predictors, such as perceived usefulness, perceived ease of use, trust, facilitating conditions, privacy concerns, and AI self-efficacy. Longitudinal or comparative studies across institutions and countries could also assess how context and time relate to AI adoption in higher education.

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